Examining the Relationship between Income

Inequality and Varieties of Crime in the United States

by

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Abstract: This paper examines the relationship between income equality and crime using U.S. statewide panel data for the years 1981 to 1999. After controlling for demographics and the rates of poverty and unemployment, I find a robust negative relationship between income inequality and the violent and property crime rates. I conclude that rising income inequality during those two decades did not lead to a concomitant increase in crime, noting that crime rates fell sharply over this time period.

Keywords: Income inequality, crime, Gini coefficient

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Introduction

The Great Recession and its anemic recovery challenged conventional wisdom regarding the relationship between economic recessions and violent crime. In 2010, for the first time in 45 years, homicide dropped from the top 15 causes of death in the U.S. (Associated Press 2012). Total homicides fell from 16,799 in 2009 to 16, 065 (Carson 2012). Murder rates continued to post declines in New York, Detroit, Washington, and other large cities. In Los Angeles, known for widespread gang and drug-related violence in 1990's, violent crimes dropped by 13.5 percent (Rubin 2012). Property crimes, which include burglary and robberies, posted declines between 3 percent and 9 percent. Despite high unemployment, public spending cuts, and a plummeting housing market in Los Angeles, overall crime declined for its ninth consecutive year. Experts cite more effective crime-fighting tactics and strict sentencing laws as chief contributors to declining trends in crime in cities (Rubin 2012).

While fears about rising crime seem to have been allayed, concerns have been growing over what many perceive to be an explosion in income inequality over the past few decades. The Congressional Budget Office (CBO) released a study highlighting the trends in the distribution of after-tax household income between 1979 and 2007 (CBO 2011). The study revealed that while all income quintiles posted gains, the top 1 percent of earners saw their incomes increase by 275 percent. The share of income drawn from labor income, which includes wages and salaries, and capital income decreased over this period, while the share of income drawn from business income and capital gains income increased. The study also examined the role of taxes and transfer payments in reducing inequality. The CBO found that of the difference between the dispersion of market income, or income before taxes and transfers, and market income plus transfers minus federal taxes, 60 percent was attributable to transfers and roughly 40 percent was attributable to federal taxes. In 1979, low-income household received half of all transfers, but this dropped to 35 percent in 2007, reflecting shifts in Social Security and Medicare payments and interest on the national debt, which are not limited to low income households. Out of 140 countries, U.S. has the 40th highest level of income inequality, as measured by the Gini coefficient (CIA 2007). While top earners likely experienced significant declines in income as a result of the recession, the general trend seems to suggest that inequality has risen.

Many sociologists and criminologists have examined the relationship between income inequality and crime. The effect of income inequality on crime will vary at national, state, and regional levels for different reasons. Researchers suggest that income inequality motivates crime because it creates a relative sense of deprivation among the poor (Weatherburn 2001). Some have argued that areas with large dispersions in income provide attractive targets for those motivated to commit crimes. Finally, researchers have also noted that income inequality can lead to high concentrations of poverty in certain areas, bringing potential offenders together (Weathernburn 2001). However, it also possible for income inequality to provide a disincentive to commit crimes. Wealthy areas may implement private protection such as alarm systems, which could significantly deter crime (Chiu & Madden 1998).

This paper explores the impact of income inequality on types of violent and property crime while controlling for demographic changes and other economic indicators. To capture the local effects of income inequality on crime, all variables are measured using statewide panel data, rather than national data, for 1981 to 1999, providing a total of 1020 observations.

Literature Review

Jogmook Choe (2008) discovered a strong relationship between income inequality and certain types of crime. She used panel data from all states and the District of Columbia for 1995 to 2004, and measured income inequality using the Gini coefficient and the ratio of different income quintiles (Choe 2008). While previous studies only measured the impacts of income inequality on violent crime, Choe's paper analyzes all seven crime categories classified under the Uniform Crime Report (UCR) from the Federal Bureau of Investigation (FBI). These crimes include murder, forcible rape, robbery, aggravated assault, burglary, larceny/theft, and motor vehicle theft. The dependent variable was measured as crime per 100,000 inhabitants in a state. Her control variables included disposable income per capita, the unemployment rate, age, education, urbanization rate, and the poverty rate. Lagged dependent variables were used to account for autocorrelation, since past crimes usually exert a strong influence on current crime rates. Among the four violent crimes, only robbery was found to have a statistically significant positive relationship with income inequality. For the property crimes, only burglary was found to have a strong relationship with income inequality. While her study provides some evidence of a relationship between income inequality and crime, she fails to consider other factors that could impact crime rates, such as variations in police employment and gun laws by state.

Jesse Brush (2007) assessed the relationship between income inequality and crime using both cross-sectional and time series analyses of U.S. counties. Countywide data could provide more meaningful results, since perceived inequality in one's neighborhood might impact crime more robustly than national or statewide inequality. Cross-sectional data proved consist with the hypothesis that income inequality impacts crime, but the time-series analysis fixed-effect model was not (Brush 2007).

The data consisted of crime rates from U.S. Census Office's County and City Data Books for 1990 to 2000. Since the crime rate variables were based on police reports, they could be underreported. This bias may also be correlated with income inequality if it is found that people in impoverished areas are less likely to report crimes, or if police in underfunded departments do not record all crimes conscientiously. Gini coefficients were used to measure income inequality, and a variable was also constructed to measure the proportion of individuals over 100,000. Controls similar to those in the Choe study were applied.

In the first model, which measured cross-sectional data for 2000, Brush discovered that counties with a greater percentage of high income-earning individuals were significantly correlated with crime. However, he did not find that the poverty rate was significantly correlated with crime. While this may indicate that there are higher returns to stealing in high-income areas, Brush also found that median incomes were positive correlated with crime. While further investigation may be needed, this could be explained by the quality of police departments' recording-keeping in high income areas. The second model, which employed the time series data, revealed that the change in income inequality has a significant negative relationship with crime. It also showed that the poverty rate had a surprisingly significant negative relationship with income inequality. The results suggest that there has been a decline in crime in the 1990's and that there are other factors which account for this trend.

While the Gini coefficient may be a useful measurement of income inequality, it does not account for wealth accumulation or additional earned income from jobs, such as health benefits. To address these concerns, Matz Dahlberg and Magnus Gustavsson analyzed the impacts of income inequality on property crime in Sweden using permanent and transitory income (Dahlberg & Gustavsson 2007). They hypothesized that transitory income, short-term changes in income, will have only negligible effects on crime. However, they expected permanent income, which includes an individual's assets or real wealth, to have a significant effect on crime. Separating the effects of both incomes accounts for biases that may occur when using total income as a measurement of income inequality. A region with low income inequality in permanent income and low crime rates could have a wide distribution of transitory income. When these incomes are aggregated, the results could show that income inequality has no effect or a negative effect on crime.

Dahlberg and Gustavsson calculated permanent and transitory income inequalities from 1974 to 2000 using individual income tax reports. Total income was measured as a log of total earnings, which includes benefits, for all jobs during the year. Individuals were disaggregated into age cohorts to account for intergenerational variation, since younger individuals who are entering the labor force are more likely to experience permanent income shocks. Permanent income was measured using a random walk and random growth model. Property crime was divided into three categories: shoplifting, burglary, and auto theft. Results revealed that an increase in permanent income inequality yields a significant positive effect on all three categories, while an increase in transitory income inequality does not yield any significant effect on any of those crimes. The authors however did not consider if permanent income inequality leads to accelerated crime rates not because it disenfranchises those at the bottom of the income distribution, but because it provides potential victims at the top of the income distribution.

Researchers Joanne Doyle, Ehsan Ahmed, and Robert Horn focused on how labor markets, income inequality, and demographics influence property crime (Doyle et al. 1999).

They used state panel data from 1984-1993 to estimate a model of property crime. Independent variables included average-market wages, sector-specific wages, unemployment rates, and the Gini coefficient. They estimated an "opportunity wage" using the average real and salary disbursement per employed worker, the unemployment rate, and unemployment compensation. The opportunity wage is based on a rational choice assumption that favorable legal opportunities to earn a wage should reduce crime since the opportunity cost of crime is higher. To reduce the possibility that higher wages may have a positive effect on property crime, since there might be more to steal in those high wages areas, they measured real per capita income as well. Finally, they disaggregated the model into sector-specific wages to account for the possibility that high-skill jobs would displace workers with low-skills, which could affect crime. Controls included police officers employed per capita.

Doyle, Ahmed, and Horn (1999) found that the proportion of young males in a population has a significant positive effect on property crime, which is consistent with previous research. Since young males typically occupy low-skilled jobs, it is not surprising that this group would try to supplement their incomes by engaging in illicit activities. The researchers also found that the proportion of young males in a population exerted a significant negative effect on violent crime, though they did not offer any explanation for this relationship. Additionally, they discovered that income inequality has no significant effect on crime, and that property crime is the most responsive to wages in low-skilled sectors. For instance, wages in wholesale and retail trade had the largest negative impact on property crime. They found that a 10 percent increase in the opportunity wage predicts a 5.8 percent decrease in crime, confirming their hypothesis that higher opportunity and the ability to participate in the labor market reduce crime. Their research suggests that poor economic conditions, rather than explicitly income inequality, incentivize the disenfranchised population to commit crimes.

Some researchers explored cross-country comparisons to determine the effects of income inequality. Pablo Fajnzylber, Daniel Lederman, and Norman Loayza specifically examined the effect of income inequality on homicide and robbery rates while accounting for GDP growth, GNP growth, education, and the rate of urbanization (Fajnzylber et al. 2002). Controls similar to the Doyle study were added. Measuring crime rates across countries can be challenging because the rate of reporting differs in each countries as well as the definitions of certain crimes. Income inequality was measured using the Gini coefficient, the ratio of income of the richest to the poorest quintile of the population, and an index of income polarization. Income polarization accounts for heterogeneity within the income quintiles themselves. This measurement is based on research that suggests that social tension within those groups could lead to violence and crime. They concluded that Gini coefficient and income polarization have a robust positive effect on increasing crime rates. However, polarization across quintiles, viz., the ratio of income of the richest to the poorest quintile, did not produce any significant effects. GDP had a significant negative effect on crime rates. Educational attainment only had a significant negative effect on the robbery rate. These results provide evidence that inequality within the quintiles, not just among them, may be an important factor in encouraging criminal activity.

Fritz Foley (2011) examined the effect of welfare payments on property crime. He analyzed daily reported incidents of crimes in 12 cities over the course of monthly welfare payment cycles. Citing studies that indicate that welfare beneficiaries often exhibit short-term impatience, Foley hypothesized that recipients consume welfare-related income quickly and attempt to supplement it with criminal income. Since they lack access to savings and credit that would offset such cash depletions, and often face poor job prospects, crime would become more attractive under these conditions. Given that most welfare programs offer payments at the beginning of the month, he expected crime to increase as the time since the last payment occurred increases. The independent variable was measured as the days that have passed since welfare was received from the Food Stamp Program, Temporary Assistance for Needy Families (TANF), or Supplemental Security Insurance (SSI) Program. Controls measured the effects of weather on criminal behavior, under the assumption that snowfall and rain would deter crime. Results confirmed Foley's hypothesis and revealed that the strongest correlation existed between the independent variable and robbery. That is, robbery increased as more days passed since the last welfare payment because robbery is more likely to yield liquid assets than other types of crime. Foley proposed increasing the frequency of welfare payments to smooth the pattern of crime and improving police deployment near the end of the month.

John Nunley, Richard Seals, and Joachim Zietz (2011) studied the effects of macroeconomic conditions on property crime using Uniform Crime Report data from 1948-2009. The macroeconomic variables included the inflation rate, an index of manufacturing unemployment, and the return on the stock market. Declining employment in the manufacturing sector disproportionately reduces labor market options for young urban males, because high wages outside of this sector usually demand higher skills. The return on the stock market variable helps account for the effects of wealth accumulation and income equality on creating attractive targets for criminals, since poor individuals generally do not participate in the stock market. Moreover, previous research also suggests that criminals are driven more by relative poverty than by absolute poverty. The percentage of young adults in the population, implemented as a control, had a significant positive impact on the larceny rate, but not on the burglary, motor vehicle theft, and robbery rates. They found that the three macroeconomic variables had a statistically significant positive effect on crime. However, the variables explain no more than 15 percent of the surge in property crimes from the 1960's to the 1980's and their fall during the 1990's. This suggests that there are other factors that influenced crimes rates during these periods, and that the variables in their model may not be economically significant even though they are statistically significant.

Some researchers have found no statistically significant relationship between income inequality and crime. Eric Neumayer (2005) analyzed the impact of income inequality on robbery and violent theft. He argued that the link between income inequality and crime across countries is spurious because income inequality is often linked with country-specific fixed effects, such as cultural differences. Crime data was gathered from the International Criminal Police Organization and United Nations Crime Surveys, which covered 59 countries. The Gini coefficient was used as the main independent variable, with GDP per capita, its growth rate, the unemployment rate, the urbanization rate, the female labor participation rate, and measures of democracy and human rights violations added as controls. An alternative income-inequality variable that measures the ratios of those in the top quintile to those in bottom was also used. Neumayer found that an increase in income leads to an increase in the violent crime rate over a range of income, but at a decreasing rate. This occurs either because higher incomes raise the value of property that can be stolen or because the reporting of such crimes is higher in richer countries. He also discovered that the relationship between the Gini coefficient and crime, which was moderately significant at the 10 percent confidence level, was surprisingly negative. Adopting a more representative sample and accounting for those country-specific fixed effects demonstrated that income inequality is not a significant predictor of crime.

Ayşe İmrohoroğlu, Antonio Merlo, and Peter Ruper (2000) developed a general-equilibrium model to investigate how crime and police expenditures are based on the distribution of income-earning abilities. Agents in the model are heterogeneous with respect to income-earning abilities and choose to engage in either legal market activities or crime. In the model, the government uses resources to redistribute income and capture criminals, activities which are financed through labor income taxes. Using 1990 state-level data, they found that property crime and the standard deviation of income are positively correlated. Welfare expenditures and police protection were similarly positively correlated. Their model found that it is possible for an increase in redistribution to increase property crime because transfer payments may subsidize criminal activities. Higher taxes to finance those subsidies also have distortionary effects on those who are participating in legal market activities. This lowers the overall output in their model, subsequently lowering total resources devoted to the apprehension of criminals. They found that an increase in the average wage rate caused an increase in the opportunity cost of engaging in crime, which resulted in a decrease in the crime rate. They concluded that the distortionary effects of the taxes and subsidies are large relative to the opportunity cost effect, causing crime to increase as subsidies increase. Their results indicate that even if excessive income inequality causes a rise in crime, policies that attempt to reduce income dispersions, such as progressive taxation and income redistribution, could possibly lead to increases in crime.

Bruce Kennedy, Ichiro Kawachi, Deborah Prothrow-Stith, Kimberly Lochner, and Vanita Gupta (1998) hypothesized that income inequality undermines social capital and leads to increased firearm homicide and violent crime (Kennedy et al. 1998). Social capital was measured using responses to the U.S. General Social Survey. The survey asked questions about their membership in voluntary groups and about their trust in the local community. The researchers calculated their own measure of income inequality from household data for 25 income intervals, which were then organized into deciles. Their index produces a percentage that represents the share of income that would have to be transferred from those above the mean income to those below the mean to achieve an income distribution of perfect equality. Firearm homicide rates were obtained for 1987-1991 from all states, as were firearm robbery and assault incidence rates for years 1991-1994 from the FBI and Uniform Crime Report. Income inequality and a lack of social capital were strongly correlated with firearm violence. A decrease in social buffers from formal and informal community networks contributes to inner-city delinquency. Dense populations, such as those found in urban areas, tend to contain high crime rates and low levels of civic engagement, though the nature of the relationship between these variables is unclear. It is possible that these areas promote withdrawal from the community precisely because of the prevalence of criminal behavior (Rosenfeld, Messner, Baumer 2001).

Determinants of Crime

In this study, I examine the relationship between income inequality and crime for all fifty states and the District of Columbia from 1981 to 1999 using data obtained from the Uniform Crime Report. The two dependent variables draw on seven types of crime measured as crime per 100,000 residents. The violent crime measure includes murder, forcible rape, robbery, and aggravated assault, whereas the property crime measure includes burglary, larceny, and motor vehicle theft. The main independent variable, income inequality, is estimated using the Gini coefficient. A Gini coefficient of “0” indicates “perfect equality,” whereas a Gini coefficient of “1” indicates “perfect inequality.” I anticipate that a higher Gini ratio would contribute to a higher crime rate, insofar as relative deprivation pushes people to crime. Controls include the poverty rate, unemployment rate, percentage of the population that is between the ages of 18 and

24, percentage of the population that is older than 65, percentage of the population that is female, and population density.

The unemployment rate captures the effects of macroeconomic downturns on crime, and the poverty rate measures absolute deprivation. The age and gender variables account for demographic differences among the states. A state with a larger percentage of 18 to 24 year olds and men might have higher rates of crime, since young males are more likely than older age groups or women to engage in delinquent acts. I use population density, measured as population per square mile, to approximate the effect of urbanization on crime. Urban areas tend to have a large polarization of income, containing clusters of low-income and high-income groups, and high crime rates. The literature suggests that there are two plausible reasons for a positive relationship between income polarization and crime rates in urban areas. Since high income groups have more resources, they represent potential victims for low-income criminals. Additionally, urban areas foster little social capital because the transition to advanced industrial economies is often associated with increasing anonymity and the loss of the social-connectedness that mitigates criminal behavior in less developed areas.

Based on previous research, I hypothesize the following model, where "c" is the intercept:

$$\textbf{[violent, property]crime} = \beta_1\textbf{gini} + \beta_2\textbf{unemployment} + \beta_3\textbf{age1824} + \beta_4\textbf{poverty} - \beta_5\textbf{age65} - \beta_6\textbf{female} + \beta_7\textbf{popdensity} + \textbf{c} + \varepsilon$$

I expect positive coefficients for β_1, β_2, β_3, β_4, and β_7, whereas I expect negative coefficients for β_5 and β_6, and that the error terms, ε, will be random-normally distributed.

Model Estimation and Interpretation of Results

I estimate the coefficients for each dependent variable using a fixed-effects model to account for heterogeneity among states in unmeasured characteristics. Hausman's test produced a Chi-squared statistic of 2040.71 for the violent-crime model and 685.84 for the property-crime model, rejecting the null hypothesis that the differences in coefficients between the random-effects models and fixed-effects models are not systematic. Regression results for the violent and property crime fixed-effects models are shown in Tables 1 and 2 respectively.

The initial results are surprising. In the violent crime model, the Gini, age 18-24, population density, and female variables have negative coefficients with strong significance at the 99 percent level. The model shows that a 1 percent rise in the Gini coefficient would lower the violent crime rate by 38.72, approximately 9.3 percent of the average violent crime rate in 2004. The elderly variable has strong positive significance at the 99 percent level. The unemployment rate and poverty rate were not significant. In the property-crime model, the Gini and population density variables have negative coefficients with strong significance at the 99 percent level. The model shows that a 1 percent increase in the Gini coefficient would lower the property crime rate by 219.11, approximately 6.3 percent of the average property crime rate in 2004. The age 18-24 and poverty rate variables were significant at the 95 percent confidence level. The unemployment rate and age 65 variables were not significant.

To determine if the results reflected heteroskedasticity, the regressions were rerun to produce robust standard errors, which are shown in Table 3 and Table 4. In the violent-crime model, population density lost its significance. In the property-crime model, AGE18-24 dropped to significance at the 90 percent level. No other significant changes occurred to the t-statistics in both models after adjusting for heteroskedasticity.

Since past crime rates are likely to influence future crime rates, I also explored the presence of autocorrelation in both models. Conducting a Wooldridge test for serial autocorrelation produced F-statistics of 150.349 and 212.7 for the violent- and property-crime models respectively, rejecting the null hypothesis that there is no first-order autocorrelation. Table 5 provides the regressions after correcting for both heteroskedasticity and autocorrelation in the violent-crime model. The Gini and AGE18-24 variables maintained their strong negative significance at the 99 percent confidence level. The Elderly variable remains significant at the 99 percent confidence level, but now holds a negative relationship with the violent crime rate, as I originally hypothesized. The female and population density variables switched to having a significant positive impact at the 99 percent confidence level.

The property-crime model also underwent several changes after adjusting for heteroskedasticity and autocorrelation, as illustrated in Table 6. AGE18-24 retained its negative relationship with the property-crime rate, but became significant at the 99 percent confidence level. The Elderly variable, which was not significant in the previous model, now held a significant negative relationship with the property crime rate at the 99 percent confidence level. The population-density variable remained strongly significant, but switched to having a positive relationship with the property-crime rate. While the unemployment rate had not been significant in the previous models, it now has strong significance at the 99 percent confidence level. As I initially hypothesized, it is positively related to the property crime rate. The model estimates that a 1 percent increase in the unemployment rate would increase the property crime rate by 23.65, or about 0.068 percent of the average property crime rate in 2004.

Conducting pairwise correlations reveals that there is some multicollinearity in the model. The results are shown in Table 7. The poverty rate has a moderately strong positive correlation with the Gini coefficient and unemployment of .57 and .53 respectively. The female variable has a moderately strong positive correlation with the Elderly variable of .59. Population density also has a moderately strong positive correlation with the Gini coefficient of .50. Since the poverty rate has a strong correlation with the main independent variable, the Gini coefficient, and is a related measure, dropping the poverty variable from the model may help isolate the impact of income inequality on crime. The effects of dropping poverty from the violent- and property-crime models, while controlling for heteroskedasticity and autocorrelation, appear in Table 8 and 9 respectively. In the violent-crime model, while there were no changes in the signs of the coefficients, the age 65 and female variables became slightly less significant, dropping to the 90 percent and 95 percent confidence levels respectively. In the property-crime model, there were no changes in significance of the variables.

Conclusion

A robust negative relationship between income inequality and crime mirrors the overall direction of these two variables from 1981-1999. The Gini coefficient rose during those decades, yet both violent and property crime rates declined significantly. However, without further investigation, I do not find the results sufficient to conclude that an increase in income inequality leads to a drop in crime, nor can I conclude that a decrease in crime causes income inequality to rise. Nonetheless, the regressions provide evidence that an increase in income inequality cannot be said to cause an increase in crime. These results are consistent with Brush (2007), who found a negative relationship between income inequality and crime using a time-series analysis. Based on the research of Steven Levitt, Brush explained that the significant drop in crime in the 1990's could be attributed to "increases in the number of police, the rising prison population, the waning crack epidemic, and legalized abortion (Brush 2007)."

The unemployment rate shares a significant positive relationship with property crime, but does not appear the have any significant relationship with violent crime. This suggests that macroeconomic conditions affect property crime, which is consistent with the findings of Nuley, Seals, and Zietz (2011). Since certain kinds of unemployment can be classified as permanent income shocks, ones that reduce wealth accumulation, these results are also supported by Dahlberg and Gustavsson (2007). The unemployment rate likely does not influence violent crime because such crime may be motivated by non-pecuniary factors, though this conjecture warrants further examination.

In addition, I find little evidence that absolute deprivation, as measured by the poverty rate, has a significant impact on crime. Given that the poverty rate has a moderately strong correlation with the Gini coefficient and the unemployment rate, it may seem surprising that these three variables do not share a similar relationship with the crime rate. However, one should note that there are a variety of factors that contribute to poverty, and the unemployment rate only represents one of these factors. It is likely that some of the other factors that contribute to poverty are not correlated with the crime rate, and therefore overwhelm the impact of the unemployment rate on crime.

Some of the results for the demographic variables mirror prior findings. Population density had strong positive significance in both the violent and property crime models, confirming previous studies which found a positive correlation between urbanization and crime rates. The percentage of females in a population also shared a robust positive relationship with the crime rate. While this result may initially seem alarming, since perpetrators are often male, it provides evidence that females provide attractive targets for criminals. That is, male criminals see larger returns from their activities by victimizing females, who are often unable to defend themselves.

Both age variables shared strong negative significance in the violent and property crime models. Since most elderly individuals are not physically and mentally capable of executing crimes, it is not surprising that the AGE65 variable shares a negative relationship with the crime rate. Moreover, the elderly generally have more wealth than younger individuals, and as a result many live in communities which are often shielded from crime. The results for the AGE1824 variable partially resemble those in the Doyle, Ahmed, and Horn (1999) paper, which found a negative relationship between the percentage of young males in the population and the violent crime rate. However, they also found a positive relationship between the percentage of young males in the population and the property crime rate. Similarly, Nunley, Seals, and Zietz (2011) discovered a positive relationship between the percentages of individuals ages 18-24 in a population and the larceny rate, though the relationship was not significant for the other property crime variables.

The models may have produced a strong negative relationship between the AGE1824 variable and the crime rate because states with large young populations may have a high percentage of those students enrolled in college. While I did not control for educational attainment, I suspect that it is negative correlated with crime rates. That is, well-educated individuals are less likely to commit crimes. It may also be true that young adults tend to move to areas, such as college towns, which already have low rates of crime. These claims however require further exploration.

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Appendix A: Data Definitions and Sources

Variable	Definition [mean; standard deviation]	Source
ViolentCrime	Violent crime rate per 100,000 people [515.76; 344.07]	Federal Bureau of Investigation
Property Crime	Property crime rate per 100,000 people [4524.33; 1219.84]	Federal Bureau of Investigation
Gini	Pre-tax, pre-transfer Gini coefficient [.395; .028]	University of Texas Inequality Project
Unemployment	Percentage of labor force that is unemployed [.062; .022]	Southern Regional Economic Board
Age1824	Percentage of population between ages 18 and 24 [.111; .018]	Census Bureau, Current Population Survey
Poverty	Percentage of households below U.S. poverty line [.135; .042]	Census Bureau, Current Population Survey
Age65	Percentage of population over age 65 [.122; .022]	Census Bureau, Current Population Survey
Female	Percentage of population that is female [.511; .01]	Census Bureau, Current Population Survey
PopDensity	Population per square mile [354.44; 1354.65]	Census Bureau, Current Population Survey

Appendix B: Tables

Table 1

Regression Results for **violentcrime** (Fixed-Effects)

Explanatory Variables	Coefficients	Standard Errors	t-statistics	Regression Statistics	
gini	-3871.662	411.1849	-9.42***	R-Squared	0.5494
unemployment	-236.1588	252.7884	-0.93	F-Statistic	31.20
age1824	-1929.222	446.0999	-4.32***	n	1020
poverty	222.6539	179.9093	1.24	Chi-Squared	2040.71
age65	5738.889	929.6821	6.17***		
female	-11726.17	2958.464	-3.96***		
popdensity	-0.1835085	0.0319331	-5.75***		
intercept	7604.615	1487.591	5.11		

Table 2

Regression Results for **propertycrime** (Fixed-Effects)

Explanatory Variables	Coefficients	Standard Errors	t-statistics	Regression Statistics	
gini	-21911.44	1962.021	-11.17***	R-Squared	0.188
unemployment	908.2505	1206.212	0.75	F-Statistic	56.01
age1824	-4262.366	2128.623	-2.00**	n	1020
poverty	-2184.946	858.4599	-2.55**	Chi-Squared	685.84
age65	-4062.542	4436.097	-0.92		
female	60772.41	14116.69	4.31***		
popdensity	-1.405781	0.1523728	-9.23***		
intercept	-16176.81	7098.229	-2.28		

* Significant at 10% level
**Significant at 5% level
***Significant at 1% level

Table 3

Regression Results for **violentcrime** (Adjusted for Heteroskedasticity)

Explanatory Variables	Coefficients	Robust Std. Errors	t-statistics	Regression Statistics	
gini	-3871.662	486.9047	-7.95***	R-Squared	0.5495
unemployment	-236.1588	254.1444	-0.93	F-Statistic	36.01
age1824	-1929.222	446.8605	-4.32***	n	1020
poverty	222.6539	278.7617	0.80		
age65	5738.889	963.2161	5.96***		
female	-11726.17	3314.674	-3.54***		
popdensity	-0.1835085	0.1375614	-1.33		
intercept	7604.615	1624.762	4.68		

Table 4

Regression Results for **propertycrime** (Adjusted for Heteroskedasticity)

Explanatory Variables	Coefficients	Robust Std. Errors	t-statistics	Regression Statistics	
gini	-21911.44	2231.962	-9.82***	R-Squared	0.188
unemployment	908.2505	1161.004	0.78	F-Statistic	44.15
age1824	-4262.366	2328.064	-1.83*	n	1020
poverty	-2184.946	932.3086	-2.34**		
age65	-4062.542	5262.585	-0.77		
female	60772.41	17719.86	3.43***		
popdensity	-1.405781	0.3700764	-3.80***		
intercept	-16176.81	8991.25	-1.80		

* Significant at 10% level
**Significant at 5% level
***Significant at 1% level

Table 5

Regression Results for **violentcrime** (Adjusted for Autocorrelation)

Explanatory Variables	Coefficients	Standard Errors	z-statistics	Regression Statistics	
gini	-993.5443	235.6482	-4.22***	Chi-Squared	66.49
unemployment	131.5582	130.1874	1.01	F-Statistic	150.349
age1824	-2152.632	435.7412	-4.94***	n	1020
poverty	91.87175	61.99912	1.48		
age65	-2177.32	669.1168	-3.25***		
female	5341.653	1688.12	3.16***		
popdensity	0.1621428	0.0401497	4.04***		
intercept	-1498.731	821.9757	-1.82		

Table 6

Regression Results for **propertycrime** (Adjusted for Autocorrelation)

Explanatory Variables	Coefficients	Standard Errors	z-statistics	Regression Statistics	
gini	-14009.98	1428.297	-9.81***	Chi-Squared	237.01
unemployment	2364.696	846.5055	2.79***	F-Statistic	212.70
age1824	-10688.49	2749.367	-3.89***	n	1020
poverty	674.6574	425.7135	1.58		
age65	-33155.78	3558.84	-9.32***		
female	34853.18	8412.779	4.14***		
popdensity	0.4349716	0.0974563	4.46***		
intercept	-3216.87	4023.026	-0.80		

* Significant at 10% level
**Significant at 5% level
***Significant at 1% level

Table 7

Pairwise Correlations

Variables	gini	unemployment	age1824	poverty	age65	female	popdensity
gini	1						
unemployment	0.1104	1					
age1824	-0.2441	0.3952	1				
poverty	0.5704	0.529	0.1849	1			
age65	0.1642	-0.2108	-0.3793	0.0522	1		
female	0.3801	0.0871	0.0611	0.2932	0.5929	1	
popdensity	0.4979	0.0947	0.1028	0.1518	0.0751	0.3995	1

Table 8

Regression Results for **violentcrime** (**poverty** dropped)

Explanatory Variables	**Coefficients**	**Standard Errors**	**z-statistics**	**Regression Statistics**	
gini	-1117.846	230.5588	-4.85***	Chi-Squared	55.39
unemployment	182.2691	120.31	1.51	n	1020
age1824	-1864.352	432.9534	-4.31***		
age65	-1372.11	708.2047	-1.94*		
female	3818.836	1856.953	2.06**		
popdensity	0.1694176	0.0472041	3.59***		
intercept	-803.8706	910.205	-0.88		

Table 9

Regression Results for **propertycrime** (**poverty** dropped)

Explanatory Variables	**Coefficients**	**Standard Errors**	**z-statistics**	**Regression Statistics**	
gini	-14554.41	1418.577	-10.26***	Chi-Squared	229.54
unemployment	2665.268	789.1485	3.38***	n	1020
age1824	-11146.71	2791.023	-3.99***		
age65	-33174.87	3820.437	-8.68***		
female	36061.02	9131.034	3.95***		
popdensity	0.4316986	0.1127898	3.83***		
intercept	-3521.997	4404.45	-0.80		

* Significant at 10% level
**Significant at 5% level
***Significant at 1% level